Today's lecture:

- Bayesian networks

Bayes Theorem:

$$P(h|e) = P(e|h) \times P(h)/P(e)$$

Or:

$$P(h|e) = P(h \wedge e)/P(e)$$

Bayesian Exercise:

2 tests are given, 25% passed both tests, 42% passed the first. What is the probability that a student who passed the first test also passed the second?

$P(passed\ both) = 0.25$

$P(passed\ first) = 0.42$

$P(passed\ both|passed\ first)$

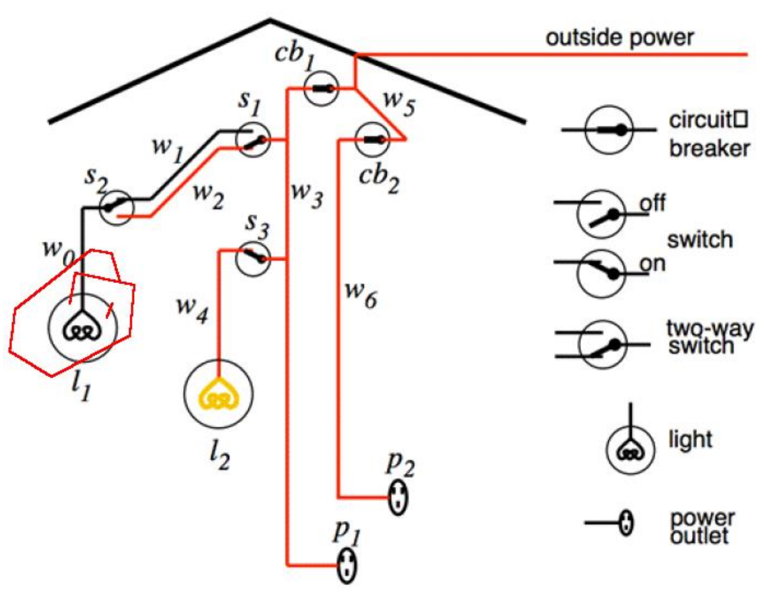
$$= P(passed\ first|passed\ both) \times P(passed\ both)/P(passed\ first) =$$

$1.0 \times 0.25/0.42 = 0.595$

Conditional Independence:

- Random var X is **independent** of Y given Z if Y's value does not affect one's belief in X's value given the value of Z:
- $P(X = x|Y = y_1, Z = z) = P(X = x|Y = y_2, Z = z) = P(X = x|Z = z)$

Example: electrical circuit:



Example of conditional independence: in the slides

Belief Networks:

- Totally order the variables of interest: $X_1, \dots, X_n$
- The parents of X_i denoted $paretns(X_i)$ are its predecessors that render X_i independent of other predecessors:

  $parents(X_i) \subseteq \{X_1, \dots, X_{i-1}\}$ and $P\left(X_i \middle| parents(X_i)\right) = P(X_i | X_1, \dots, X_{i-1}\}$
- So $P(X_1, \dots, X_n) = \prod_{i=1}^{n} P\left(X_i \middle| parents(X_i)\right)$
- A **belief network** is a DAG where rand vars are nodes and edges are from parents to children

… (wimba got stuck)

Pruning irrelevant variables:

Suppose we want to compute $P(X|e_1, \dots, e_k)$

- Prune variables with no observed or queried descendants
- …